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Exploring the Dynamic Nexus between Industrialization, Environmental Pollution and Health Expenditure in Bangladesh: A VECM Approach

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Abstract: Industrialization boosts economic growth but causes pollution, harming public health and raising healthcare costs. Inflation compounds this challenge, as rising prices make healthcare services, both preventive and curative, less accessible and affordable for the public. This research aims to identify the impact of industrialization and environmental pollution on health expenditure in Bangladesh. The study used time series data collected from 1997–2023. The study uses Johansen's co-integration test, which identifies one co-integrated equation, and applies the Vector Error Correction Model (VECM) for estimation. The VECM results show a strong long-term connection. The error correction coefficient for health expenditure (which is the dependent variable) is negative and significant at 1%, showing a stable long-term connection between environmental pollution, industrialization, inflation, and health expenditure. Furthermore, all independent variables—industrialization, pollution and inflation—have a positive and significant impact on health expenditure. There is also evidence of short-term causality among these variables. To address these issues, the study recommends that the Bangladeshi government adopt targeted policies, including promoting sustainable agriculture practices, expanding renewable energy sources, and restoring ecosystems. Enhancing urban green spaces, regulating industrial waste, and investing in healthcare infrastructure are crucial steps to mitigate pollution's health impacts and support sustainable economic growth. Community engagement in environmental practices would support these efforts, fostering sustainable development and economic resilience.

Introduction

The dual nature of industrialization as both an engine of economic and societal growth and a source of environmental and public health concerns. Rapid industrial growth in Bangladesh, particularly in urban areas, has led to substantial increases in air and water pollution. Major sources of pollution include the textile, leather, and chemical industries; greenhouse gases, as well as urban waste and emissions from transportation and power generation, are released into the air, water, and soil. The resulting environmental degradations not only drive climate change but also have long-term adverse effects on ecosystems and human health, including respiratory diseases, cardiovascular issues, and waterborne infections. This escalating health burden has driven up healthcare demand, directly increasing both household and national health expenditures. Households face rising out-of-pocket expenses for treatment, impacting their financial stability and creating a complex challenge for sustainable development.

The study highlights Bangladesh as the world's most polluted country, where fine particulate air pollution ($PM_{2.5}$) poses severe health risks. If Bangladesh met the WHO's air quality guideline of 5 µg/m³, the average Bangladeshi would live 6.8 years longer. However, air quality varies across regions, with Gazipur, near Dhaka, experiencing even higher pollution levels that reduce life expectancy by 8.3 years. This underlines both the national and regional health crises caused by extreme air pollution and the urgent need for measures to reduce $PM_{2.5}$ levels across the country (AQLI, 2023).

The World Bank's Bangladesh Country Environmental Analysis (CEA) report highlights severe pollution and environmental health risks in Bangladesh,

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disproportionately affecting the poor, young children, the elderly, and women. According to the report, lead exposure, poor sanitation and hygiene, contaminated water, and air pollution cause 5.2 billion days of disease annually and approximately 272,000 premature deaths. An estimated 17.6% of Bangladesh's GDP was lost due to health and environmental costs in 2019. Household and outdoor air pollution was responsible for about 55% of premature deaths and 8.32% of GDP losses (World Bank Report, 2024).

A recent study by the Centre for Policy Dialogue (CPD) reveals that residents of Dhaka spend approximately Tk 4,000 annually on diagnosing and treating health issues linked to air pollution—almost double the government's per-person health budget of Tk 2,228 for the current fiscal year. This financial burden reflects the significant health impact of pollution, which raises the risks of serious conditions like stroke, heart disease, lung cancer, and respiratory diseases, both chronic and acute, such as asthma. Common symptoms from these pollution-related illnesses include respiratory issues (coughing, difficulty breathing, sore throat), chest pain, and eye irritation. The findings underscore both the economic and health challenges posed by poor air quality in Dhaka (TBS, 2023).

There are some studies conducted on the impact of industrialization and environmental pollution on health expenditure. Economic growth and aging populations drive healthcare costs in emerging countries, while the impacts of industrialization, agriculture, and technology vary by quantile. Industrialization affects health expenses unidirectionally, while bidirectional causality exists between health expenditure and GDP per capita, as well as between health expenditure and agricultural activities. The study applied quantile regression and Pooled Mean Group tests to analyse healthcare expenses and examine causal relationships (Zhou et al., 2020). The study confirms an asymmetric relationship in China between CO_2 emissions, environmental pollution, and household health expenditure. Positive shocks increase health spending, while negative shocks reduce it. Bi-directional causality exists among health spending, CO_2 emissions, and pollution. This suggests that higher CO_2 emissions and environmental pollution lead to increased household health expenditures for Chinese residents. The study used NARDL and Granger causality to explore the dynamic, asymmetric relationship between CO_2 emissions, pollution, and health expenditure (Zeeshan et al., 2021; Prasad et al., 2023). The study found that CPI (Consumer Price Index) inflation has a greater impact on healthcare expenditure than PCE (the personal consumption expenditure price index) inflation, with healthcare expenditure considered a necessary good (short-run income elasticity < 1). VECM results indicate strong short-run Granger causality from economic growth and price index to healthcare expenditure. Additionally, impulse response function analysis reveals strong positive long-run bidirectional Granger causality between healthcare expenditure and economic growth while showing strong negative long-run causality between healthcare expenditure and inflation (Namini, 2018).

The paper analyses India’s health expenditure (1990–2017) using polynomial regression and ARIMA models, revealing a polynomial trend with two structural breaks. It finds long-run causal relationships with HDI, GDP per capita, CO_2 emissions, energy use, life expectancy, and education expenditure. Short-run causalities exist from HDI and life expectancy to health expenditure. The VECM indicates instability and non-stationarity, showing health expenditure's response to changes in energy use, life expectancy, and education expenditure (Bhowmik, 2020). The study examines the asymmetric impact of environmental quality on health expenditures in Turkey (1975–2019) using the NARDL model. Positive environmental pollution shocks increase health expenditures in the long run, while natural resource and trade openness shocks have inverse effects. The findings highlight the importance of environmental protection for future health expenditure efficiency (Demir et al., 2023). The paper analyses the impact of economic growth and environmental quality on health expenditure in MENA (Middle East and North Africa region) countries (1995–2014) using the ARDL method. It finds that income and CO_2/PM10 emissions significantly raise health expenditure, with inelastic income elasticity, suggesting that health expenditure is less sensitive to income changes in the region (Yazdi et al., 2017). This study examines the relationship between environmental quality, economic growth, and health expenditure in 47 African countries (2000–2018), using static and dynamic estimation methods. It finds that economic growth and poor environmental quality (especially CO_2 emissions) significantly increase health expenditure. The study emphasizes the need for clean energy policies to reduce pollution and support sustainable growth (Ibukun et al., 2020). This study examines the long-term relationship between environmental quality and socio-economic factors on health expenditure in Malaysia using ARDL analysis. It finds that GDP, CO_2, NO_2, SO_2 emissions, fertility, and infant mortality rates significantly affect health expenditure. Notably, SO_2, fertility, and infant mortality have substantial impacts, highlighting the

importance of sustainable development for future generations (Abdullah et al., 2016). This study examines the dynamic relationship between CO_2 emissions, health expenditures, and economic growth in Pakistan (1995–2017) using the ARDL model. It finds significant long- and short-term causal links, with bidirectional causality between health expenditures, CO_2 emissions, and growth, recommending policies to control pollution and health costs without limiting growth (Wang et al. 2019). The study analysed the short- and long-term effects of economic growth, environmental pollution, and energy consumption on health and R&D expenditures in ASEAN countries. Long-term results showed significant positive impacts on both expenditures, while short-term impacts were limited to R&D, with no effects on health expenditures (Haseeb et al., 2019).

The study identified a short-run relationship among health expenditure, GDP growth, and CO_2 emissions. It found bidirectional causality between health expenditure and GDP in Germany and the U.S., CO_2 emissions and GDP in Canada, Germany, and the U.S., and health expenditure and CO2 emissions in New Zealand and Norway (Wang et al., 2019). The paper analyses the impact of air pollution on medical expenditures in eastern, central, and western China. It finds a positive correlation in the eastern and central regions, while the western region shows a non-linear threshold effect, indicating a complex relationship that informs healthcare budgeting for policymakers (Shen et al., 2021). This paper examines the impact of economic growth, environmental pollution, and non-communicable diseases (NCDs) on health expenditures in EU countries (2000–2014) using the Panel ARDL method. Economic growth influences health expenditures in both short and long runs, while CO_2 emissions have opposing short- and long-term effects on health costs (Badulescu et al., 2019). This paper analyses the causal relationships between environmental pollution and healthcare expenditure in Taiwan (1995–2016) using wavelet analysis. It finds varying links influenced by economic growth and specific events, indicating that higher government health spending may increase demand for environmental quality, with significant implications for policymakers at multiple levels (Wu et al., 2020).

This research analyses the impact of the environment, life expectancy, and real GDP per capita on health expenditures in 27 EU member states (2000–2018). It finds significant short-run causality from emissions, life expectancy, and GDP to health spending, with positive effects from life expectancy and GDP at the country level (Bayar et al., 2021). This article investigates the relationship between environmental governance, public health expenditure, and economic growth in China using an OLG-DGE model. Findings suggest that pollution emissions harm public health and economic growth. Environmental taxes improve health but create trade-offs with output, while increased public health expenditure positively impacts health status, depending on the level of environmental taxes (Zhang et al., 2023). The study finds that CO_2 emissions are positively linked to per capita health expenditure across 87 countries. In low-income and OBOR countries, forestation is associated with reduced health expenditures. The analysis, using GMM and control variables, highlights income-specific environmental and health expenditure dynamics (Anwar et al., 2021). The study finds that declining ecological quality in China (2009–2019) increases residents' health expenditures. Environmental effects are more pronounced in economically undeveloped and environmentally focused regions. Robustness tests confirm that improving environmental conditions can reduce health costs, providing key insights for policy-making (Ma et al., 2024). The study of 28 OECD countries (2002–2018) finds that renewable energy reduces pollution and improves public health, with long-run causality from CO_2 emissions and renewable energy to healthcare spending. Investment in renewable energy enhances healthcare outcomes and promotes economic growth (Mujtaba et al., 2020). The study reveals a long-run relationship between per capita health expenditure and explanatory variables, with CO_2 having the highest impact. The effect of these variables is stronger in the long run than in the short run, emphasizing environmental quality as a key determinant of health expenditure in developing countries (Yahaya et al., 2016). The study analyses the impact of carbon emissions and energy use on health expenditure in Bangladesh (2000–2020). It finds that a 1% increase in CO_2 and fossil fuel use raises health costs by 0.95% and 2.67%, while a 1% rise in renewable energy use reduces health expenditure by 1.44% (Raihan et al., 2022). The study examines the effects of structural change and environmental pollution on health expenditure (1995–2019) across 115 countries. It finds that manufacturing and service value-added increase health costs, while economic globalization reduces them. Recommendations include adopting green production techniques and better abatement policies in all economies (Fonchamnyo et al., 2022).

The study examines health expenditure, economic growth, and CO_2 emissions in 26 OECD countries (1992–2014). It finds a long-term co-integration relationship, with elasticity coefficients of 0.188 (economic growth)

and 0.012 (CO_2 emissions). Both factors causally increase health expenditure, indicating their significant interrelationship over time (Govdeli, 2019). This study uses diagnostic testing, correlation analysis, and structural equation modelling to explore the relationships among trade openness, energy consumption, CO_2 emissions, and health expenditures in Southeast Asia. It finds that pollutant emissions directly impact health spending, while trade and energy consumption influence it indirectly, with energy consumption as the mediator (Akbar et al., 2020). The study examines the relationship between economic growth, health expenditures, environmental pollution, gross fixed capital formation, and labour force in E7 countries (2000–2018). It finds significant positive elasticity coefficients and establishes causal links: economic growth influences CO_2 emissions, which subsequently affect health expenditures, highlighting the need for pollution-reducing policies (Govdeli, 2023). This study uses a panel vector autoregressive model to analyse economic growth, healthcare expenditure, and CO_2 emissions in Asia-Pacific countries (2000–2019). It finds that economic growth boosts healthcare spending, while CO_2 emissions negatively affect growth. The results emphasize the need for policies that improve healthcare and reduce emissions simultaneously (Yuan, 2023).

According to the evaluated empirical literature that was reviewed, the majority of the study focused on the fact that economic growth and pollution are primary drivers of healthcare costs globally, with an inelastic effect on spending, particularly in emerging markets. Some of the researchers studied that CO_2 emissions and pollution significantly increase health expenditures, as observed in China, Turkey, and Malaysia, while renewable energy can lower these costs, as seen in the OECD. Few researchers focused on the fact that industrialization drives healthcare costs up, while agriculture shows bidirectional effects. A small number of researchers discussed that positive environmental shocks (e.g., increased pollution) raise health expenses, whereas negative shocks lower them, indicating a complex interaction between environmental quality and health spending. Some of the researchers concentrated on the importance of sustainable policies, such as pollution control and renewable energy adoption, to manage healthcare costs without stunting growth. Overall, they emphasize the need for integrated economic and environmental policies to address rising healthcare costs and reduce the health impacts of environmental degradation. This study aims to determine how pollution and industrialization affect health spending in Bangladesh. The study will proceed as follows: the objectives are first outlined, followed by the research methodology. The results will be discussed, and the paper will conclude with managerial implications, limitations, and recommendations for future research on the connections between economic growth, environmental quality, and healthcare costs.

Objectives of the Study

The general objective of the study is to investigate the impact of industrialization and environmental pollution on health expenditure in Bangladesh.

The particular goal of this research is

1. To examine the co-integration between industrialization, environmental pollution and health expenditure in Bangladesh.
2. To test the short- and long-term relationships between industrialization and CO2 in connection to health spending using Bangladeshi data.

Materials and Methods

Sources of Data

Annual time-series data was collected from 1997 to 2023 to examine the effect of industrialization, environmental pollution, and inflation on health expenditure in Bangladesh. The four variables used in the study are industrialization, environmental pollution, inflation, and health expenditure. The study used secondary data obtained from the World Bank World Development Indicator (WDI) and Bangladesh Economic Review 2005 and 2023. The study has a total of 26 observations. Microsoft Excel and Stata/MP 13.0 have been used to conduct all econometric tests.

Table 1 provides a comprehensive overview of the variables under investigation in this study, along with their respective abbreviations, descriptions, measurements, and sources of data.

Table 1. Variables Definition.

Variables	Identifier	Source of Data	Details
Industrialization	Ind	Bangladesh Economic Review 2005 and 2023	Industrialization (Including Mining and quarrying, Manufacturing, Electricity, gas, steam and air condition, Water supply; sewerage, waste management

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			and Construction) in billion taka
Environmental Pollution	CO_2	WDI	CO_2 emissions (metric tons per capita)
Inflation	Inf	WDI	Inflation, consumer prices (annual %)
Health Expenditure	HE	WDI	Current health expenditure (% of GDP)

Figure 1 illustrates the study's three independent variables— industrialization, environmental pollution and inflation —as well as its single dependent variable, health expenditure

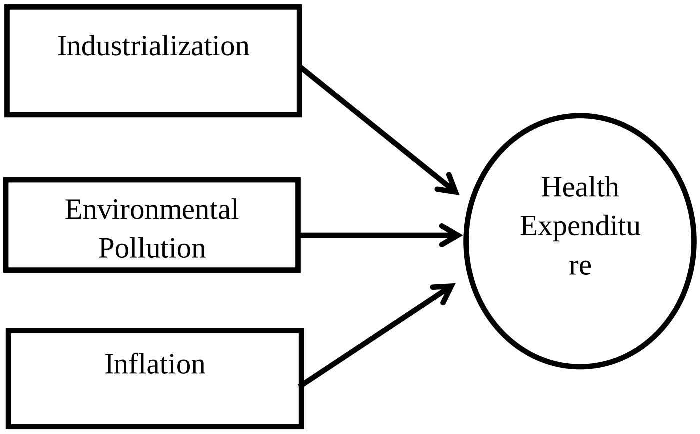


Figure 1. Proposed framework of factors influencing health expenditure in Bangladesh from 1997 to 2023.

Model Specification

The model used for empirical estimation is depicted below:

HE = f (Ind, CO_2, Inf) …………………………………. (1)

The following econometric equation is assessed for the above variables and their proxies:

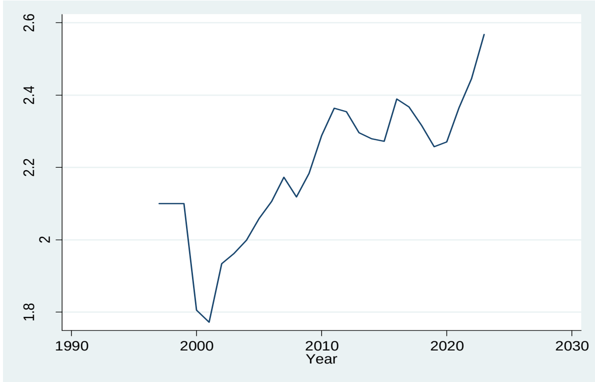
$HE_t = \beta_0 + \beta_1 Ind + \beta_2 CO_2 + \beta_3 Inf + \mu_i$ ……………..... (2)

The logarithmic form of the variables can be presented as follows;

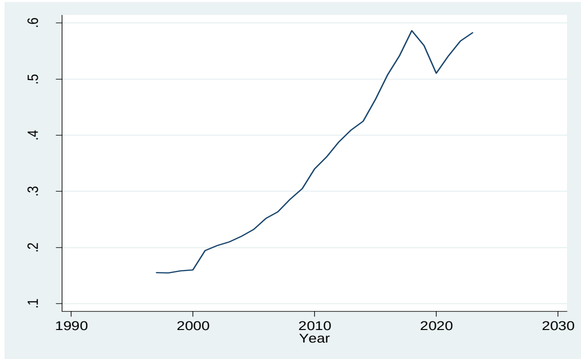
$lnHE_t = \beta_0 + \beta_1 lnInd_t + \beta_2 \ln CO_{2t} + \beta_3 lnInf_t + \mu_t$ …….(3)

Where βo is the intercept; β_1, β_2, and β_3 are coefficients, the parameters of the explanatory variables while μt is the error term, t is the time period and ln denote natural logarithm.

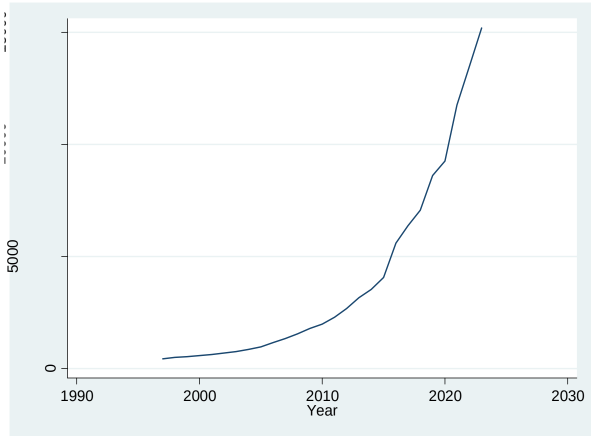
Trends in the Data



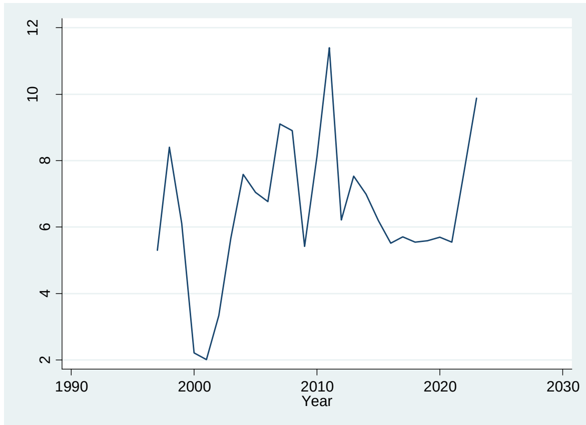
HE (a)



CO_2 (b)



Ind (c)



Inf (d)

Figure 2. Trend in HE, CO_2, Ind and Inf from 1997-2023.

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Health spending as a percentage of GDP has risen over time, with some cyclical trends, as seen in panel (a) of figure 2. The higher trend in recent years may be a sign of greater budgetary priority for health or rising healthcare costs. Panel (b) shows a consistent rise in CO_2 emissions per person over time, particularly after 2000. After 2010, the slope seems to get steeper. Emissions per capita appear to peak about 2020 at roughly 6 metric tons, followed by a sharp decline and subsequent rebound. The fluctuations between 2020 and 2023 (as projected) might indicate instability or significant events affecting emissions (e.g., global economic disruptions, policy changes, or environmental regulations). Industrialization is trending upward in Panel (c), and the sharp rise after 2020 points to exponential growth, which could be a sign of increased economic activity or production. A number of variables, including the economy's recovery from shocks like technological and policy-driven advancements, could be responsible for the more pronounced increase beyond 2020. The graph shows the steady but steady expansion of industrialization prior to 2020, pointing to the more rapid developments that followed. Additionally, panel (d) demonstrates that there were multiple rises and dips in inflation between 1990 and 2012. Around 2010, there was a notable peak that may have been caused by large regional or worldwide economic events, such as the 2008 financial crisis. Between 2012 and 2020, inflation was more constant, ranging between 5% and 6%, which may be a result of better policy and economic recovery. After 2020, inflation is expected to increase by over 10% as a result of pandemic-related disruptions (supply chain problems, fiscal reactions, etc.).

This study examines the effects of inflation, environmental degradation, and industrialization on health spending in Bangladesh through a number of tests. Descriptive statistics, Unit root analysis, ADF test, Johansen co-integration test, and Vector Error Correction Model (VECM). Furthermore, diagnostic checking procedures were conducted to assess the study's dependability.

Unit Root Test

This stage of the estimation procedure tests the stationarity of the variables employed in the study. By using the Augmented Dickey-Fuller (ADF) unit root test, which was proposed by Dickey & Fuller (1981), it is possible to ascertain the order of integration of the data series. In order to test for short-run dynamics and long-run relationships among time series variables, the time series properties of each variable are estimated by the unit autoregressive tests, i.e., whether a time series variable is stationary. Suppose the time series are found to be stationary. In that case, it means that their variance, mean, and covariance are constant over time and that the result obtained from their analysis is reliable and can be used to predict future economic activities of the economy. If the stationarity is not confirmed at Level, first-order differencing should be carried out to achieve the variables' stationarity. The three types of different regression forms of ADF are as follows:

1) Without Drift and Trend : $\Delta Y_t = \delta Y_{t-1} + u_t$ (4)

2) With Drift : $\Delta Y_t = \beta_1 + \delta Y_{t-1} + u_t$ (5)

3) With Drift and Trend: $\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t$ (6)

Where t is the time or trend variable. In each case the hypotheses are:

Null Hypothesis: H_0: $\delta = 0$ (i.e. there is a unit root or the time series is nonstationary)

Alternative Hypothesis: H_1: $\delta < 0$ (i.e. there is no unit root or the time series is stationary)

We accept the alternative hypothesis, H_1 and reject the null hypothesis, H_0 only if the p-value is less than the 5% significance. Rejection of null-hypothesis, meaning that the variables are stationary. (*Gujarati and Porter*. *Basic Econometrics*. Fifth Edition.)

The ADF (Dickey and Fuller 1981) test is conducted through the following models:

$$\Delta Y_t = \beta_0 + \delta Y_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta Y_{t-i} + u_t \tag{7}$$

where m is the number of lags in the dependent variable, u_t is a white noise error term, and Δ is the first difference operator. According to the hypothesis test, H_0 implies Y_t has a stochastic trend, while H_1 implies Y_t is stationary. The ADF statistic is obtained from the OLS t-statistics testing $\delta = 0$ in equation (7). If Y_t is stationary around a deterministic linear time trend, then the trend't' i.e., the number of observations must be added as an explanatory variable. Alternatively, (7) can be written as

$$\Delta Y_t = \beta_0 + \alpha_0 t + \delta Y_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta Y_{t-i} + u_t \tag{8}$$

In equation (8), Y_t is a random walk with drift around a stochastic trend. Here α_0 is an unknown coefficient, and the ADF statistic is the OLS t-statistic testing $\delta = 0$ in (8).

Lag Order Selection Test

A lag-order selection test was conducted to obtain the optimum lag lengths to include in both co-integration test and VECM. The sequential likelihood-ratio (LR) test, the Akaike information criterion (AIC), the Hannan–

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Quinn information criterion (HQIC), the Schwartz Bayesian information criteria (SBIIC), and the final prediction error (FPE) were used to determine the number of lags.

Co-integration Test

The Johansen co-integration test is a multivariate extension that allows the model to have more than a co-integration vector; it determines if the model is co-integrated using the maximum likelihood approach. The purpose of the co-integration test is to study the long-term association of the dependent and independent variables. The co-integration test is conducted if the variables are stationary at the first difference I (1) and not at Level I (0).

Vector Error Correction Model (VECM)

If the time series data are nonstationary at the level form and stationary at first difference and if they are co-integrated into the long run by Johansen co-integration test and then it can be easily applied the Vector error correction model. This model is also used to distinguish between long-term and short-term causality among variables. All incorporated variables are found to be stationary at first difference and co-integrated in the long run. Accordingly, the vector error correction model is applied to analyse the following relationships:

$$\Delta HE_t = \alpha + \sum_{i=1}^{k-1} \delta_i\, \Delta HE_{t-i} + \sum_{j=1}^{k-1} \theta_j\, \Delta Ind_{t-j} + \sum_{m=1}^{k-1} \gamma_m\, \Delta Co2_{t-m} + \sum_{n=1}^{k-1} \varphi_n\, \Delta Inf_{t-n} + \lambda ECT_{t-1} + \varepsilon_t$$

Transforming all variables of this equation into log form, the model is rewritten as follows:

$$\Delta \ln H E_t = \alpha + \sum_{i=1}^{k-1} \delta_i\, \Delta \ln H E_{t-i} + \sum_{j=1}^{k-1} \theta_j\, \Delta \ln I nd_{t-j} + \sum_{m=1}^{k-1} \gamma_m\, \Delta \ln C o2_{t-m} + \sum_{n=1}^{k-1} \varphi_n\, \Delta \ln I nf_{t-n} + \lambda ECT_{t-1} + \varepsilon_t$$

Where,

α -The vector of constant term

$\delta_i, \theta_j, \gamma_m$ and ϕ_n - Short-run dynamic coefficients of the model's adjustment long-run equilibrium.

k-1 = the lag length reduced by 1

λ = speed of adjustment parameter with a negative sign

ECT_{t-1} = The error correction term is the lagged value of the residuals obtained from the co-integrating regression of the dependent variable on the regressors, which contains long-run information derived from the long-run co-integrating relationship.

ε_t = Random error term

t = Time trend

Diagnostic Checking

Diagnostic tests such as the Breusch-Godfrey Serial Correlation Lagrange-Multiplier tests, normality tests, and stability tests are applied to check the model's adequacy.

Breusch-Godfrey Serial Correlation LM Test

The Breusch-Godfrey serial correlation LM test is a statistical test used to detect autocorrelation in regression models. It is particularly valuable in dynamic models where lagged values of the dependent variable are included as regressors. The test helps identify if residuals exhibit autocorrelation, which can lead to biased and inconsistent Ordinary Least Squares (OLS) estimates. This test is used to test the null hypothesis that there is no autocorrelation up to a certain number of lags. It is particularly useful in the context of time series analysis because it can be applied even when the series is non-stationary.

Normality Test

The normality test computes a series of test statistics for the null hypothesis that the disturbances in a VECM are normally distributed. For each equation and all equations jointly, up to three statistics may be computed: a skewness statistic, a kurtosis statistic, and the Jarque–Bera statistic. By default, all three statistics are reported; if you specify only one statistic, the others are not reported. The Jarque–Bera statistic tests skewness and kurtosis jointly. The single-equation results are against the null hypothesis that the disturbance for that particular equation is normally distributed. The results for all the equations are against the null that all K disturbances have a K-dimensional multivariate normal distribution. Failure to reject the null hypothesis indicates a lack of model misspecification.

VECM Stability Test

VECM Stability Test uses the coefficient estimates from the previously fitted VEC model to back out estimates of the coefficients of the corresponding vector autoregressive (VAR) model and then compute the eigenvalues of the companion matrix. This test shows how the companion matrix is formed and how to interpret the resulting eigenvalues for covariance-stationary VAR models.

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Results and Discussion

This section of the study deals with the presentation of the estimation results and consequently discusses the results as estimated on the subject matter, “the effect of industrialization, environmental pollution, and inflation on health expenditure in Bangladesh.”

Descriptive Statistics

The descriptive statistics of the variables are narrated in Table 2. This table demonstrates that the data set contains no unusual patterns. The mean statistics for all variables are consistent. The standard deviation shows that all of the variables are stable, no unstable variables exist. It also narrated that the value of environmental pollution is the lowest, while the value of industrialization is the highest.

Table 2. Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
lnHE	27	.7820002	.0899675	.5721196	.943074
$lnCO_2$	27	-1.136179	.4678148	-1.865619	-.5341665
lnInd	27	7.703712	1.125155	6.077252	9.628714
lnInf	27	1.808141	.3935046	.6967276	2.433189

Unit Root Test

Table 3 depicts the estimation results of the unit root test through the application of the Augmented Dickey-Fuller (ADF) stationarity test at 5% critical value.

Table 3. Result of Augmented Dickey-Fuller (ADF) Test.

Variables	Without Trend		With Trend	
	Level	First Difference	Level	First Difference
lnInd	2.158**	-3.218***	-2.641	-4.155**
$lnCO_2$	-1.399*	-3.421***	-1.226	-3.822**
lnInf	-1.762**	-3.764***	-2.124	-3.669**
lnHE	-1.282	-3.547***	-3.550*	-4.514***

Note: (i) Figures within parentheses indicate lag length chosen by the Akike information criterion (AIC); (ii) ***, ** and * denote rejection of the null hypothesis of unit root at the 1%, 5% and 10% significance level respectively.

According to the estimation results, in case of without trend, Ind, CO_2, and Inf were stationary at level (at 5%, 10%, and 5%, respectively) and first difference (all variables are stationary at 1%). However, HE is stationary at the first difference (1% crucial value) but not at level. In case of with trend, Ind, CO_2, and Inf are not stationary at level but stationary at first difference (at 5% critical value). In contrast, HE is stationary at level (at 10% critical value) and first difference (at 1% critical value). This claim is evidenced by the ADF statistic values, critical values, and p-values of the respective variables estimated in the test, respectively (see table 3 above). After first differencing, the variables showed evidence of integration of the same order, indicating that they had long-term characteristics and that their mean, variance, and covariance are constant overtime at that level. As a result, the series is sufficiently dependable to be used for additional estimation of the behaviours of the variables used in the research.

Optimize Lag Selection

Table 4. Summary of the lag selection criterion results.

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	37.7644				6.2e-07	-2.93603	-2.88637	-2.73856
1	144.48	213.43	16	0.000	2.4e-10	-10.8244	-10.576	-9.83698*
2	163.007	37.054	16	0.002	2.2e-10*	-11.0441	-10.5971	-9.26682
3	181.777	37.539	16	0.002	2.7e-10	-11.2849	-10.6393	-8.71772
4	206.741	49.928*	16	0.000	3.6e-10	-12.0644*	-11.2201*	-8.7073

‘*’ Indicates lag order selected by the criterion

Determination of optimum lag by comparing every lag to the criteria used is the first step taken in VECM model checking, which is most important in time series data analysis. The results in Table 4 show the maximum values from each of the information criteria are shown by a star (*), which indicates the lag optimum is at lag 4 by the selection criteria of the AIC (Akaike information criterion), HQIC (Hannan-Quinn information criterion), and LR (sequential modified Likelihood Ratio test statistic (each test at 5% level). However, the lag optimum is at lag 1 by the selection criteria of the SBIC (Schwarz Bayesian Information Criteria), and the lag

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optimum is at lag 2 by FPE (Final Prediction Error). In this study, the optimal lag of 4 was selected using the Akaike Information Criterion (AIC) (The results are presented in Table 4). Thus, further tests were conducted with a lag length of 4 and a single co-integration relationship between variables. The Vector Error Correction Model (VECM) was used to check whether the order of the fitted model was appropriate.

Johansen Co-integration Test

In order to investigate the long-run relationship between health expenditure and industrialization, environmental pollution, and inflation, the variables have first to be tested for co-integration. If the series are co-integrated, then the corresponding error correction term and an error correction model must be constructed. The Johansen Co-integration Test is used to determine if the variables co-move towards a long-run equilibrium. The results in Table 5 suggest that the variables are co-integrated with a co-integration rank of order 1. These findings indicate that the appropriate model to fit in the data is VECM.

Table 5. Result of the Johansen Co-integration Test.

Maximum rank	Parms.	LL	Eigenvalue	Trace statistic	5% Critical value
0	52	166.00623		81.4690	47.21
1	59	192.52943	0.90038	28.4226*	29.68
2	64	202.61301	0.58390	8.2554	15.41
3	67	206.70483	0.29939	0.0718	3.76
4	68	206.74073	0.00312		
* Selected rank					

Vector Error Correction Model

The presence of co-integration amongst variables suggests that the variables have a long-run relationship; hence, the VECM is appropriate for modelling the relationship between health expenditure and industrialization, environmental pollution, and inflation. Further, the VECM also reports the short-run relationship amongst variables and how they adjust towards a long-run equilibrium. From Table 6, the co-integrating equation between health expenditure and industrialization, environmental pollution, and inflation for Bangladesh in the period of 1997–2023 is given as:

$ect_{t-1} = lnHE_{t-1} - 0.0917002lnCo2_{t-1} - 0.0522184lnInd_{t-1} - 0.0956649lnInf_{t-1} - 0.4308558$

So, $lnHE_{t-1} = 0.4308558 + 0.0917002lnCo2_{t-1} + 0.0522184lnInd_{t-1} + 0.0956649lnInf_{t-1} + ect_{t-1}$

Table 6. Co-integrating equation - Johansen normalization restriction imposed.

Beta	Coef.	Std. Err	z	P>|z|	[95% Conf. Interval]
_ce1					
lnHE	1				
$lnCO_2$	-.0917002	.0462261	-1.98	0.047	-.1823017 -.0010987
lnInd	-.0522184	.0200957	-2.60	0.009	-.0916053 -.0128316
lnInf	-.0956649	.0080877	-11.83	0.000	-.1115164 -.0798134
_cons	-.4308558				

Table 6 shows that at the 5% level of significance, every coefficient is significant. The coefficients can be understood as long-run elasticities when the variables are logarithms and only one co-integrating vector is calculated. There is a positive relationship between health expenditure and all other independent variables (industrialization, environmental pollution, and inflation). Therefore, a 1% increase in environmental pollution is expected to result in a 0.0917002% increase in health expenditure. The health expenditure rises by 0.0522184 percent for every 1% industrialization increase, and the 1% increase in inflation increases health expenditure by 0.0956649 percent. In general, the HE mentioned above equation result is satisfactory because health expenditure has a correct positive sign with industrialization, environmental pollution, and inflation.

Table 7 shows the results for the individual adjustment of the variables in the short run towards the long-run equilibrium. Table 7 specifies that the coefficient of the error correction term for health expenditure as the dependent variable is negative and statistically significant at a significance level of 1%. This suggests that there is a long-run relationship between industrialization, environmental pollution, inflation, and health expenditure.

Table 7. Adjustment Parameters.

	Coefficient	Standard Error	Z statistics	P value	[95% Conf. Interval]	
D_lnHE_ce1 L1	-1.079457	.3652214	-2.96	0.003	-1.795278	-.3636361
lnHE						
LD	.6540971	.256235	2.55	0.011	.1518857	1.156309
L2D	.3416272	.3026271	1.13	0.259	-.251511	.9347654
L3D	.0016766	.1994132	0.01	0.993	-.3891662	.3925194
$lnCO_2$						
LD	.3566829	.1133095	3.15	0.002	.1346004	.5787654
L2D	-.0170013	.1123609	-0.15	0.880	-.2372246	.2032219
L3D	| .040154	.087811	0.46	0.647	-.1319524	.2122603
lnInd						
LD	-.3626223	.1173992	-3.09	0.002	-.5927204	-.1325241
L2D	-.2996431	.1445126	-2.07	0.038	-.5828825	-.0164036
L3D	-.3687544	.1236872	-2.98	0.003	-.6111768	-.126332
lnInf						
LD	-.0862336	.0446524	-1.93	0.053	-.1737508	.0012835
L2D	-.0500304	.0347958	-1.44	0.150	-.118229	.0181682
L3D	-.005937	.0265573	-0.22	0.823	-.0579883	.0461143
_cons	-.012127	.0315772	-0.38	0.701	-.0740173	.0497632

According to table 7, in the short run, the first lag (LD) of lnHE shows a significant relationship (coef. = 0.654, p = 0.011), while the second lag (L2D: P-value = 0.259) and third lag (L3D: P-value = 0.993) of lnHE suggest a lack of statistical significance. The first lag (LD) of $lnCO_2$ has a significant effect (coef. = 0.357, p = 0.002) on health expenditure at the 1% level, while the second and third lags are not significant. All three lags of land, say the first lag (LD: coef. = -0.363, p = 0.002), the second lag (L2D: coef. = -0.300, p = 0.038), and the third lag (L3D: coef. = -0.369, p =.003), are significant with p-values below 0.05, implying their effect on the dependent variable is consistently significant. Most lags of lnInf are non-significant except the first lag of lnInf (LD), which is borderline significant with a p-value of 0.053.

Table 8 shows that we reject the null hypothesis in all cases because the P value < at the 1%, 5%, and 10% significance levels, respectively. Therefore, there is overall short-run causality between industrialization, environmental pollution, inflation, and health expenditure.

Table 8. Summary of the overall short-run causality among health expenditure, industrialization, environmental pollution and inflation.

Null and Alternative Hypothesis	Chi-sq	df	P-value
H_0:There is no overall short-run causality between Health Expenditure and Industrialization H_1: There is an overall short-run causality between Health Expenditure and Industrialization	13.56	3	0.0036
H_0:There is no overall short-run causality between Health Expenditure and Environmental Pollution H_1: There is an overall short-run causality between Health Expenditure and Environmental Pollution	10.55	3	0.0144
H_0:There is no overall short-run causality between Health Expenditure and Inflation H_1: There is an overall short-run causality between Health Expenditure and Inflation	6.95	3	0.0735

Diagnostic Test

Autocorrelation Test

The Breusch-Godfrey serial correlation LM test is used to test the presence and/or absence of serial correlation in the residuals. The null hypothesis can be rejected if the p-value is less than the significant level of 5%. The null and alternative hypotheses are as follows:

H_0: There is no serial correlation of any order
H_2: There is serial correlation in the residual

Table 9. Lagrange-multiplier test result summary.

Lag	P-value
1	0.59484
2	0.63900

The null hypothesis states that no autocorrelation is present at lag order. From table 9, at lag 1 and 2, p values

are insignificant. Therefore, accept the null hypothesis. Hence, at both lags, the VECM model is free of the problem of autocorrelation.

Normality Test

The error terms of the VECM models should ideally be normally distributed. If the error terms are not normally distributed, the parameter estimates will not be efficient; however, the results will still be consistent. Skewness, Kurtosis and Jarque-Bera tests can be applied to test their normality. Using these tests, we test the null hypothesis that the error terms are normally distributed. The null and alternative hypotheses are as follows:

H_0: The error terms are normally distributed

H_2: The error terms are not normally distributed

Table 10. Results of the normality tests.

Equation	Jarque-Bera test			Skewness test			Kurtosis test		
	Chi-sq	df	(p-value)	Chi-sq	df	(P-value)	Chi-sq	df	(P-value)
D_ln HE	0.933	2	0.62723	0.306	1	0.58030	0.627	1	0.42841
D_ln CO_2	1.411	2	0.49380	0.753	1	0.38566	0.659	1	0.41704
D_ln Ind	1.096	2	0.57822	0.870	1	0.35082	0.225	1	0.63517
D_ln Inf	0.813	2	0.66601	0.558	1	0.45503	0.255	1	0.61371
ALL	4.253	8	0.83364	2.487	4	0.64698	1.766	4	0.77875

According to Table 10, the results of all the tests show that the error terms are normally distributed because all P values > 0.05. Hence, we cannot reject the null hypothesis of normality of the error terms, and we conclude that errors are not skewed or kurtotic.

VECM Stability Test

The VECM stability condition states that the model will have "K-r" unit moduli. Here, "K" is the number of endogenous variables in the model, and "r" is the number of co-integrating vectors. In this study, the number of endogenous variables, K = 4, and the number of co-integrating vectors, r = 1. So, it will have exactly 3 unit moduli (K-r = 4-1=3).

Table 11. The VECM stability Test result.

Eigenvalue	Modules
1	1
1	1
1	1
-.6099417 + .6648084i	.902219
-.6099417 - .6648084i	.902219
-.1572736 + .8648213i	.879006
-.1572736 - .8648213i	.879006
.7412565 + .1502736i	.756335
.7412565 - .1502736i	.756335
.1641279 + .727738i	.746016
.1641279 - .727738i	.746016
.4431928 + .5326704i	.692934
.4431928 - .5326704i	.692934
-.594958 + .2521635i	.64619
-.594958 - .2521635i	.64619
-.220239	.220239
The VECM specification imposes 3 unit moduli.	

Table 11 shows that the stability results of the VECM with four lagged differences revealed three unit moduli, which satisfies the stability condition for our VECM model. This also means that the specification of the number of co-integrating vectors is correct. Table 11 demonstrates that the modulus of each eigenvalue is strictly less than one, hence the estimated VECM is stable. Again, the graph of the eigenvalues in Figure 3 shows that none of the remaining eigenvalues appears close to the unit circle. The stability check does not indicate that the model is misspecified.

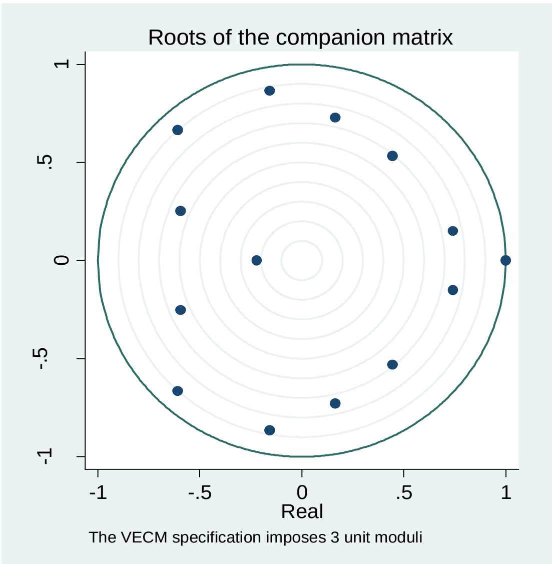

Figure 3. Stability of variance.

Conclusions

The main objective of the study is to investigate the impact of industrialization and environmental pollution on health expenditure in Bangladesh from 1997 to 2023. Another purpose of the study is to test the short-run and long-run relationship between CO_2 and industrialization

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with respect to health expenditure using Bangladeshi data. This study got some findings after analysing the data. The result of the ADF test showed that all variables are stationary at the 1st difference. As a result, Johansen's co-integration technique was used and indicated that there is one co-integrated equation in the model. Therefore, the VECM is used for the estimation. The VECM estimation shows that the coefficient of error correction with health expenditure as a dependent variable is negative and statistically significant at 1%, implying a robust long-run relationship between industrialization, environmental pollution, inflation, and health expenditure. The results also show that there is a significant positive relationship between health expenditure and all other independent variables (industrialization, environmental pollution, and inflation). Moreover, the results also indicate that there is overall short-run causality between industrialization, environmental pollution, inflation, and health expenditure. Diagnostic tests were also carried out to check the credibility of the study.

Based on these findings, the study, therefore, recommends that Bangladesh's government reverse environmental degradation through targeted, timely policies. Prioritizing sustainable agriculture—such as crop rotation and organic methods—can combat soil depletion and water contamination. Expanding renewable energy, like solar and wind, would reduce reliance on fossil fuels, lowering air pollution and emissions. River and wetland restoration can enhance water quality, support biodiversity, and mitigate flooding, building resilience against climate impacts. Increasing urban green spaces and regulating industrial waste can improve air quality and support public health and investment in healthcare infrastructure to mitigate pollution's health impacts. Engaging communities through education on environmental conservation can amplify these efforts, fostering sustainable practices at local levels. With coordinated policies and effective implementation, the government can significantly address and reverse its environmental challenges. If unchecked, pollution and health-related spending could slow economic growth in Bangladesh. High health expenditures reduce funds available for other development needs, creating a cycle of poverty and poor health outcomes in heavily polluted regions.

The study's key limitations include only the use of 26-year intervals. Collecting more frequent time series data could yield more authentic, precise results, enhancing the reliability of the findings. Additionally, the study does not consider various critical variables associated with industrialization, environmental pollution, and health expenditure, limiting the depth and practical applicability of its conclusions. To address these issues, the authors recommend that future research incorporate a broader range of variables and finer-grained time intervals. This approach would allow for a more comprehensive analysis, supporting more nuanced insights and better informed decisions in practice.

Conflicts of Interest

The author confirms no financial or personal conflicts influenced the study, ensuring transparency and credibility in the research's design, execution, interpretation, and reporting.

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